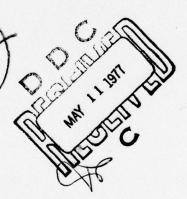




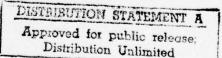
## HUMAN PERFORMANCE CENTER DEPARTMENT OF PSYCHOLOGY

The University of Michigan, Ann Arbor

A Psychophysical Analysis of Complex Integrated Displays



MARY HARDZINSKI & ROBERT G. PACHELLA





Technical Report No. 59 February 1977

#### THE HUMAN PERFORMANCE CENTER

#### DEPARTMENT OF PSYCHOLOGY

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# THE UNIVERSITY OF MICHIGAN COLLEGE OF LITERATURE, SCIENCE AND THE ARTS DEPARTMENT OF PSYCHOLOGY

### A PSYCHOPHYSICAL ANALYSIS OF COMPLEX INTEGRATED DISPLAYS

Mary Hardzinski and Robert G. Pachella

HUMAN PERFORMANCE CENTER--TECHNICAL REPORT NO. 59

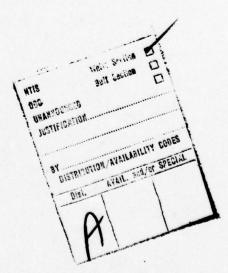
February, 1977

This research was supported by the Office of Naval Research, Department of Defense, under Contract No. No. 176-C-0648 with the Human Performance Center, Department of Psychology, University of Michigan.

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#### **ABSTRACT**

Five types of complex integrated displays were subjected to multidimensional scaling analyses. The display types were selected to be representative of a variety of characteristics that can result when dimensions are combined in an integrated fashion. These characteristics included perceptual separability, familiarity, emergent properties and perceptual interaction among dimensions. Of primary interest was the question of whether or not the Minkowski scaling metric would be diagnostic or predictive of any of these characteristics, as previous literature had indicated. The results showed that in virtually all cases the Euclidean metric produced better fits than the City-Block metric. The qualitative interpretability of the individual dimensions of the display proved to be of much greater utility for assessing perceptual characteristics. Representative analyses of individual subject data are presented and the implications of the results for display design are discussed.



#### INTRODUCTION

The purpose of the research described in this report is the development of a data base for integral and separable dimensions of display types, where the criteria for integrality and separability are independent of performance demands required of the subject. The research deals with integrated multidimensional displays; that is, situations where each variable or dimension of a multi-variate problem is mapped into a dimension of a single, unitary display. Ideally, such a display would allow any part of the information presented to the observer to be apprehended in a single spatial-temporal perceptual act. Further, integrated multidimensional displays provide an opportunity to maximize the ease with which relationships among variables can be apprehended to the extent that these relationships can be represented by perceptual relationships among the dimensions in the display. The extent to which the information can be integrated on a perceptual level depends on the relative integrality of the dimensions comprising the display. A pair of physical dimensions is said to be integral if they combine to form a new psychological attribute.

However, a pair of integral dimensions will interfere with each other when an observer is trying to make judgments on the information contained in only one of the dimensions and must ignore irrelevant information from the other. In this case, the problem is not one of integrating information across dimensions, but of being able to obtain information from each dimension of a unitary, multidimensional display. Optimal performance for such a problem would involve displays comprised of separable dimensions; that is, physical dimensions that form independent psychological attributes of the display.

The problem then is one of developing optimal display types for the variables of a complex problem and the type of information processing demands the problem requires of the observer. In the attempt to develop guidelines for the construction of such display types based on subject performance with various task demands, it is necessary to develop criteria for specifying display types in terms of the integrality and separability of the dimensions comprising the displays.

One method that has been used in the past to try to specify the manner in which physically specified dimensions are mapped into relevant attributes in a psychological space is through the use of multidimensional scaling. The basic idea was developed by Shepard (1964). In that paper, he argued that the form of the psychological metric relating the physical attributes of a multidimensional display to each other might be a function of the particular attributes involved. Shepard suggested that the combination of some attributes in a display would lead to a psychological space with a Euclidean metric of stimulus similarity, while other combinations would result in a different, perhaps City-Block, metric. Thus he inferred that there were two types of attributes; "those that are related as homogeneous, unitary wholes and those that tend to be analyzed into perceptually distinct components or properties [p. 80]". The first he termed 'unitary' and the second 'analyzable'. These refer to the integral vs. separable distinction we are trying to clarify here.

Figure 1 illustrates how the similarity of multidimensional stimuli generated from integral or separable attributes may be conceived. This diagram describes the relationship between three displays, A, B, and C. Display A differs from B only on attribute X, the degree of this perceived dissimilarity being represented as dx. Likewise, display A differs from C only on attribute Y, with dy as a measure of the perceived degree of

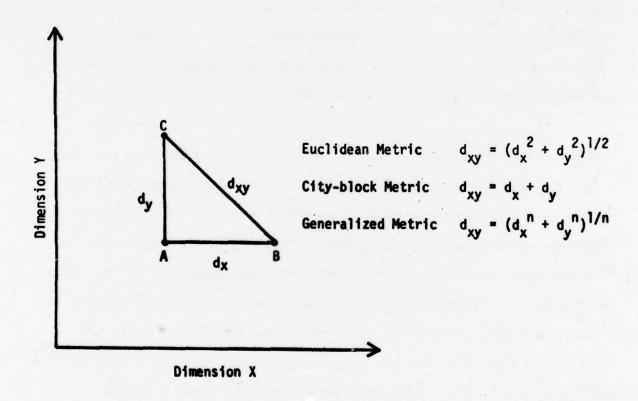


Figure 1. The geometry of multidimensional similarity showing the various ways the perceived similarity of stimuli differing on two dimensions may be related to the perceived similarity of stimuli that vary on each dimension seperately. (Adapted from Garner, 1974)

dissimilarity. Knowing the values of dx and dy the question is: What is the value of dxy, the degree of perceived dissimilarity between displays B and C, which differ on both attributes, X and Y, simultaneously?

Distances in a psychological space can be described with a generalized metric, the Minkowski metric, such that  $dxy = (dx^{N} + dy^{N})^{1/N}$  (see Torgerson, 1958). If N = 2 then the psychological space described by the metric is Euclidean in nature. Judgments of dissimilarity within a pair of displays can be thought of as the distance according to the Pythagorean relation between the displays as they are mapped into the psychological space. Alternatively, if N = 1, we have the City-Block metric. The perceived dissimilarity between displays B and C is assumed to be the sum of the dissimilarities for the pairs A-B and A-C. This method assumes that judgments of dissimilarities between members of a pair of displays can be converted into a measure of psychological distance. The value of the exponent in the Minkowski metric that best describes these distance measures is an indication of the nature of the psychological space and dimensional structure of the stimulus displays. A Euclidean space implies the conclusion that we are dealing with dimensions that are integral or unitary. Integral dimensions combine to form a new dimension so that measures of dissimilarity are a direct function of the distance between two stimuli in the psychological space. This also means that the physical dimensional structure is not particularly descriptive of the psychological attribute structure and, among other things, observers will have difficulty making judgments based on physical dimensions. If the proper metric to describe the psychological space is the City-Block metric, then the dimensional structure is separable in nature: The physical dimensions comprising the display lead to independent psychological dimensions. The psychological space is truly multidimensional

in nature, and observers must base their judgments on each of the several dimensions.

Much previous work that has utilized the multidimensional scaling technique to investigate the nature of a psychological space has characteristics which tend to limit its usefulness for the particular application that we are dealing with here. One such subset of research has utilized physically well-specified displays of low dimensionality. Usually work has been done with displays consisting of only two or three dimensions (e.g., Hyman & Well, 1967, 1968; Cohen & Jones 1974; Shepard, 1962, 1964). Hyman & Well (1967), for example, studied the metric properties of displays composed of two dimensions: Munsell color patches varying in size and chroma, parallelograms varying in size and tilt, or circles with an inscribed radius varying in diameter of circle and angle of radius (after Shepard, 1964). They found, in agreement with other investigators, that Euclidean space was appropriate for judgments of the color patches, but that the City-Block space was appropriate for judgments of geometric forms which vary on perceptually distinct dimensions. It is possible then to use the scaling metric to distinguish the dimensional structure in a stimulus display. So far, however, this has only been done with displays that vary on only two or three dimensions.

Another subset of research utilizing multidimensional scaling techniques has dealt with displays of unknown physical or psychological dimensions.

Usually in this type of research a scaling metric is chosen in advance. The purpose of the analysis is to determine the dimensionality of the psychological space, and to interpret (i.e., give a label to) the resultant psychological dimensions.

For example, Abelson & Sermat (1962) attempted multidimensional scaling of similarity ratings for thirteen faces that differed according to emotional

expression. The Euclidean scaling data was best fit using six dimensions. However, only two of these were interpretable and accounted for 75% of the variance of the data. They labeled these dimensions as pleasantness and attentiveness, and suggested that the other dimensions were perhaps non-Euclidean.

Jones & Young (1972) used a multidimensional scaling technique which yields Euclidean distance functions to determine the dimensions of interpersonal perceptions. Subjects were asked to rate the similarities of pairs of people chosen from the laboratory staff. The resulting psychological space was fit with three dimensions interpreted as status, professional interests, and political persuasions.

Stenson (1968) scaled similarity judgments using the Euclidean distance function of 20 random outline shapes drawn according to Method 4 of Attneave & Arnoult (1956). He recovered six psychological dimensions from the scaling analysis. Four complex physical factors accounted for 2/3 of the variance of the intersection of the physical and psychological spaces. The factors were described as complexity, curvature, curvature dispersion, and straight-length dispersion.

Hyman & Well (1968) discovered that enhancing the distinctiveness of color dimensions (value and chroma) or the perceptual separability of the dimensions allowed an observer to shift from the Euclidean distance structure to the City-Block. However, the introduction of noise into the system caused a shift back to the Euclidean structure. Arnold (1971) scaled judgments of similarity among English words. His analysis included a discussion of the effect of different values for the exponent in the Minkowski metric on the fit of the psychological space to similarity judgments. The worst fit occurred with N=2, and the best fit with N=32. He concluded

that N > 1 indicates that there is too much information in the stimulus set for the subject to process adequately.

The problem we are dealing with in the present research involves mapping known physical dimensions into a psychological space. Our purpose is to investigate well-specified generating procedures for displays of high dimensionality that yield different types of psychological spatial configurations. This involves discovering the dimensional structure (i.e., whether integral, separable, or a combination) for complex displays with at least five specifiable dimensions. Second we want to know what sort of scaling metric will apply to the configuration in such an instance. And finally, we have to examine the correspondence of the <u>perceivable</u> attributes to the specified physical dimensions.

#### STIMULUS DISPLAYS

In order to investigate these questions we have developed five multi-dimensional display types each of which has certain desirable characteristics useful to the study of the correspondence of specified physical dimensions with psychological attributes. The nature of the present exercise is to investigate the diagnosticity of the scaling metric for determining the dimensional structure of displays of high dimensionality. The particular dimensions and stimuli used were constructed to exhibit various different aspects of integrality and analyzability.

<u>Faces</u> - A set of schematic faces was developed based on the work of Chernoff (1973) which could vary in nineteen continous dimensions, including four specifying the outline of the face and several for the position, size, and other aspects of the eyes, eyebrows, nose, and mouth. Table 1 describes the nineteen parameters and their relation to the attributes of the face. Figure 2 presents faces generated using ten of the possible dimensions.

Table 1

Nineteen Possible Dimensions for Generating Schematic Faces\*

#### Outline of face

- 1. face size
- 2. ration (H/W) of face (amount dimple is pinched in)
- 3. location of dimple
- 4. eccentricity of upper ellipse (H/W)
- 5. eccentricity of lower ellipse

#### Nose

- 6. length of nose
- 7. width of nose

#### Mouth

- 8. location of mouth
- 9. curvature of mouth
- 10. length of mouth

#### Eyes and Eyebrows

- 11. height of eyes
- 12. separation of eyes
- 13. slant of eyes
- 14. length of eyes
- 15. eccentricity of eyes
- 16. location of pupils
- 17. height of eyebrows
- 18. slant of eyebrows
- 19. length of eyebrows

<sup>\*(</sup>Adapted from Chernoff, 1973)

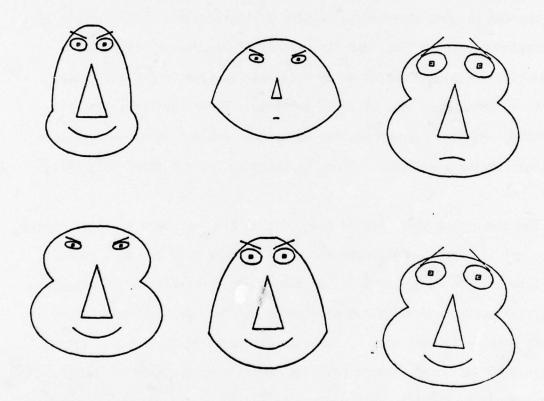
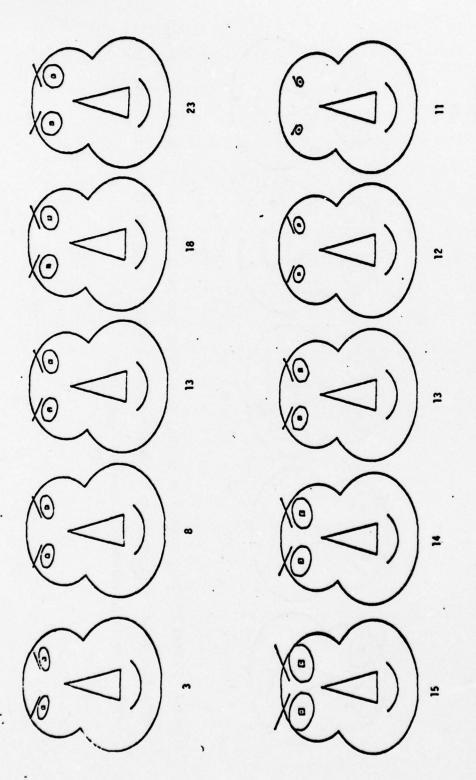


Figure 2. Examples of possible faces created by varying 10 dimensions: four having to do with face outline, three for the eyes and eyebrows, two for the mouth, and one for the noselength.

For the purposes of our research subsets of faces were composed that varied on only two dimensions at a time, with five levels spanning the range of variation on each dimension. One subset of 25 faces orthogonally varied eye length and eye eccentricity which were thought to be relatively integral. All other dimensions having to do with the face outline, feature position, and other aspects of the nose and mouth were held constant or were correlated with the two varying dimensions. Figure 3 illustrates the five levels of eye length on the top line, and five levels of eye eccentricity on the bottom line. A second subset of 25 faces varied nose length and mouth curvature, which were thought to be analyzable since they were spatially separated. Again, other dimensions were held constant or were correlated with the varying dimensions. Figure 4 presents typical faces with these values.

The dimensions that vary in the faces of Figures 3 and 4 -- eye length and eccentricity and nose length and mouth curvature -- are all simple attributes of the face. That is, each controls the variation in a single facial feature. An examination of Figures 3, 4 and particularly Figure 5a reveals a quite salient and more complex attribute of the faces. This attribute is emotional expression. The emotional expression of each face is determined by specific combinations of levels on each of the individual features of the face, with the eyes and mouth probably playing a disproportionately large role in determining emotional expression.

The attribute of emotional expression is a higher order attribute than the simple dimensions corresponding to single facial features. It is composed of a combination of simple dimensions, but knowledge of the level of any one of those dimensions does not allow prediction of the exact expression the entire face adopts. Because of this aspect of emotional



has five values of eccentricity at constant length. The bottom row has five values of length at Figure 3. Subset of 10 faces created by varying eye length and eye eccentricity. The top row constant eccentricity.

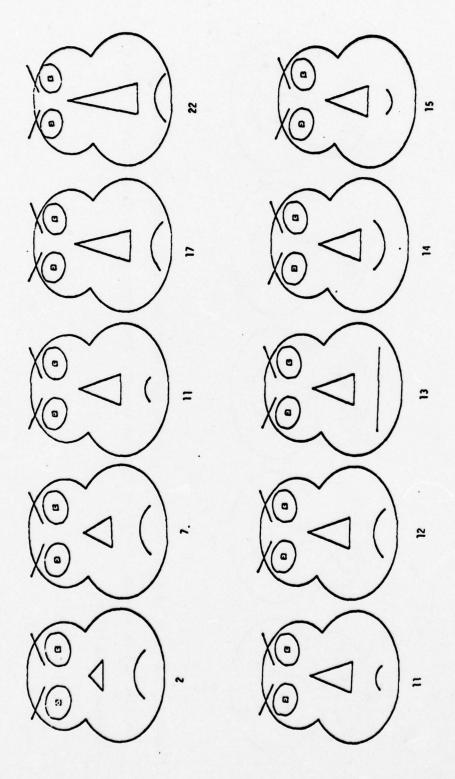
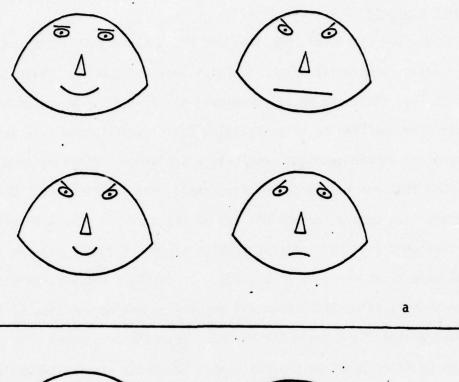


Figure 4. Subset of faces created by varying nose length and mouth curvature. The top row represents five values of nose length at constant mouth curvature. The bottom row represents five values of mouth curvature with constant nose length.



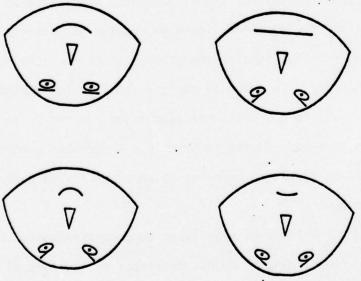


Figure 5. a. Faces with emergent property of emotional expression created by varying mouth curvature and eye and eyebrow tilt.

b. Faces of 5a turned upside down.

expression, and because expression is highly salient, it can be termed an emergent property of the stimulus.

A possible effect of this emergent property is that it may result in the relative integrality of the features that compose it. While these features (eye slant and mouth curvature) are spatially separated and would therefore be expected to be analyzable, their contribution to a salient higher-order attribute might result in a preferred processing mode in which the features are perceived as a whole, not individually. On the basis of recognition memory for upright and inverted faces Carey & Diamond (1977) have concluded that the internal representation of faces includes configurational aspects of the face as a whole. In addition there is evidence from lesian studies (Kin, 1970) that the perception and recognition of faces is mediated by the right posterior cortex. Thus the perceptual advantage enjoyed by faces might be destroyed when the faces are turned upside down. Figure 5b consists of the faces of figure 5a rotated 180 degrees. It is apparent that this rotation impairs the perception of emotional expression in the faces. Therefore, in order to analyze the effects of configurational aspects of the stimuli (e.g., emotional expression) on the perception of simple dimensions, the experiments in which eye length and eccentricity, and nose length and mouth curvature were varied were replicated with the faces presented upside down.

THE VECTOR GROUP - Three display types were constructed using five vectors emanating from a central point, separated by an angle of 72°. The length of each radius was 1, 2, 3, or 4 units from the central point. Thus, each display type consisted of five dimensions (the vectors) each varied along four values.

These display types are unique in that each is generated using the same five physical dimensions; i.e., length of a vector emanating from a

central point, so that each display type is equivalent in an information theory sense. However, very different results obtain depending upon the emergent properties of the different display types that express the values along each of the five dimensions.

<u>Spokes</u> - One display type generated by this technique consists of the five vectors presented alone. This is the most obviously analyzable of the three display types (see Figure 6b). To make similarity judgments subjects can directly compare each of the five dimensions.

<u>Polygons</u> - The second set of stimuli was constructed by connecting the endpoints of the five vectors in the stimuli of the first set. The generating vectors were then eliminated, and the result is a set of five-sided polygons such as those presented in Figure 6a. The dimensions comprising the stimuli are more integral for the polygons than for the spokes. That is, sides of the polygons combine more dramatically than do the arms of the spokes to form configurational attributes of regularity and shape.

<u>Combined</u> - The third set of stimuli was constructed by embedding the vectors within their polygons, essentially a combination of the preceding two display types (see Figure 6c). This display type provides the potential for analyzability found with the spokes plus the configurational characteristics of the polygons. In addition, a higher-order attribute of depth emerges with these stimuli, which is quite intuitively compelling.

Ellipses - The fifth display type developed consists of simple ellipses that vary along five dimensions: area, defined as  $\frac{\|ab\|}{2}$  where  $\underline{a}$  is the length of the major axis and  $\underline{b}$  is the length of the minor axis; eccentricity, defined as  $[1 - b^2/a^2]^{1/2}$ ; orientation of the major axis, defined as the angle from the horizontal; vertical position on the screen; and horizontal position on the screen. Each dimension could assume four values. Some

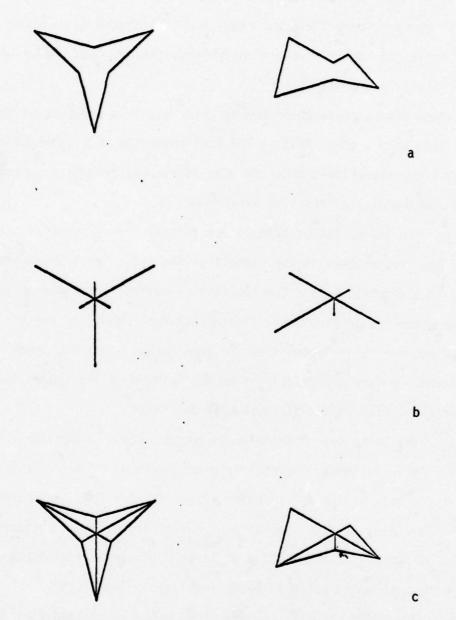


Figure 6. Examples of stimuli from the vector group generated by varying the lengths of five vectors emanating from a central point. The stimuli in each group were created with the same five vectors.

- a. Polygons created by connecting the endpoints of imaginary vectors.
- b. Spokes representative of the actual vectors.
- c. Combined group includes both the polygons and their vectors.

examples are presented in Figure 7. The ellipse display type is perhaps the simplest in terms of straightforward analyzability of the component dimensions. There is little possibility for the physical dimensions to combine into higher order psychological attributes that cannot be pre-determined by specifying the physical dimensions. With this set of stimuli, we have the opportunity to study the possibility of low level interaction between physical dimensions that is not confounded by "emergent" attributes of the display. However, the dimensions of area and eccentricity of the ellipses are basically the same physical dimensions as eye length and eye eccentricity of the faces. Thus, it is possible to determine the differential psychological effects of embedding these physical dimensions in the context of emergent properties provided by the faces.

The total possible number of stimuli that can be constructed in the vector group display types and with the ellipses is over 1000 for each set. This is an unmanageable number to use for obtaining similarity judgments on pairs of stimuli. To reduce the number of pair judgments required of the subjects, a process of stimulus selection was carried out according to a Latin Square design. Using this procedure, a 16-cell matrix was obtained; each cell contained a value for each of the five dimensions. The values were then rearranged to obtain another 16-cell matrix that was as different as possible from the original, i.e., no more than two values for any two dimensions that occurred together in the first matrix could occur together in the second. In this manner, we obtained a set of 32 distinct stimuli for the four display types. The obtained Latin Squares are represented in Table 2. These stimuli were the most representative, yet manageable samples that could be obtained from the original sets. These 32 stimuli made 496 distinct pairs of stimuli (irrespective of position in the pair) which could then be shown to subjects for similarity judgments.

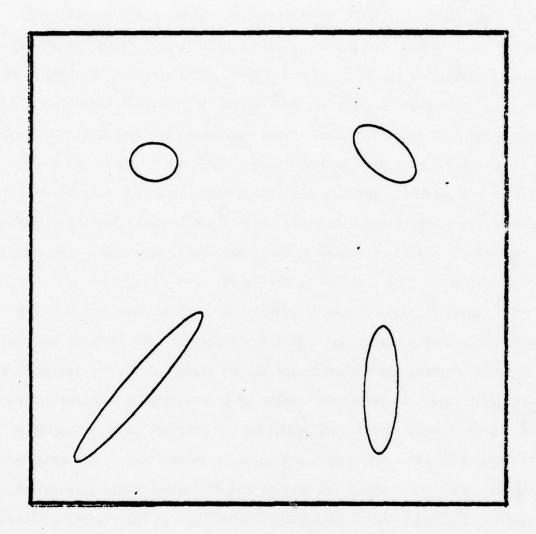


Figure 7. Examples of ellipses varying in size, eccentricity, orientation, and horizontal and vertical position within the square. The stimulus in the upper right corner represents the smallest and least eccentric ellipse. The stimulus in the lower right corner represents the largest and most eccentric ellipse.

Table 2

Two Latin	Squares	for Choosing	Stimuli*
11111	12222	13333	14444
21234	22143	23412	24321
31342	32431	33124	34213
41423	42314	43241	44132
•			
11243	12134	13421	14312
21122	22211	23344	24433
31414	32323	33232	34141
41331	42442	43113	44224

\*The numbers define values 1 to 4 for each of five ordered dimensions making up a display.

#### Technique

Each of the five display types were subjected to multidimensional scaling analysis based on subjects' similarity judgments of pairs of stimuli taken from each set of displays. This procedure gives a psychophysical measure designed to determine the dimensional structure of the stimuli in each set and the mapping of the physical dimensions into psychological attributes. The psychophysical technique provides an objective phenomenal description of the stimulus set as opposed to an indirect assessment based on performance measures such as reaction time or percent error. The dimensional structure obtained from the multidimensional scaling procedure will be used to validate later research which will incorporate performance measures.

Data were collected from sets of subjects, numbering between four and by showing them all pairs of stimuli from the set of each display six, type. They were asked to rate the similarity of the pair on a scale from 1 - 10, with 1 being the most similar, and 10 being the most dissimilar. Subjects were familiarized with the stimuli that made up the stimulus pairs prior to the data collection. The n(n-1)/2 similarity judgments made by each subject were tabulated in an n by n matrix. This matrix was used as input to the Guttman-Lingoes non-metric multidimensional scaling program MINISSA (Guttman, 1968; Roskam and Lingoes, 1970). This program generates a constellation of points in a multidimensional space in which each point corresponds to a stimulus. In this space, two stimuli that are judged to be relatively similar are represented by points that are relatively near each other. Also, pairs of dissimilar stimuli are represented by pairs of points that are far apart in the space. This means that the greater the judged similarity of a pair of stimuli, the closer their

represented points. This monotonicity requirement restricts the positioning of the points. For example, assume the judged similarity of two stimuli, call them A and B, is 7, and the program places their corresponding points  $P_A$  and  $P_B$ , so they are 2 units apart. The requirement of monotonicity means that all stimulus pairs with similarity ratings 8, 9, or 10 should be represented by points that are more than 2 units apart in space. Similarly, stimulus pairs with ratings from 1 to 6 should be represented by points that are less than 2 units apart.

Deviations from this rule are summarized in a goodness-of-fit measure. This measure is called the stress of the configuration of points (Kruskal, 1964), with a stress of zero meaning a perfect fit of similarity judgments and interpoint distances. MINISSA computes stress using the following formula:

stress = 
$$\left(\sum_{i < j} \left(d_{ij} - d_{ij}^{\star}\right)^{2} / \sum_{i < j} d_{ij}^{\star}\right)^{2}\right)^{1/2}$$

where  $d_{ij}^{\star}$  is the distance measure if the configuration perfectly satisfied the monotonicity requirement. The multidimensional scaling algorithm is therefore a method to create a constellation of points with a minimum stress. This algorithm starts with an initial configuration of points that is created by a random placement of the stimulus points in the space. The dimensionality of the space is specified by the user. The stress is computed for this configuration. The points are then moved around in an iterative fashion creating new configurations that will tend to reduce the stress at each iteration. The procedure continues until a configuration of minimum stress is found for the given dimensional space. In the analysis of the similarities data, two parameters, dimensionality and metric, were varied in an attempt to generate configurations of low stress and high heuristic value for dimension interpretability.

The dimensionality of the space is a crucial parameter in the heuristic value of the point constellation since N points may always be scaled in a space of N - 1 dimensions with a zero-stress configuration. However, this constellation would probably be of minimal value in helping to visualize the relation among stimuli. Therefore fewer dimensions are used in attempting to generate a low-stress configuration. Often one reduces the dimensionality until it can no longer be reduced and still have the algorithm generate a satisfactory low-stress configuration. The heuristic value of this configuration may be assessed and a decision is made to accept this configuration or to accept a configuration of lower dimensionality with higher stress and greater heuristic value. Many times, the minimal dimensionality is determined by plotting the stress by the number of dimensions as in Figure 8. As the number of dimensions increases, the stress decreases. This relationship, however, is usually not linear and therefore a break or elbow can be noted. This point represents the number of dimensions at which further increases in dimensionality will not lead to a significant reduction in stress.

In most spaces a Euclidean metric is used to compute the interpoint distances given the locations of the points in the constellation. This metric is equivalent to the "usual", intuitive, real-world distance measure. In a two dimensional Euclidean space, the distance between points at coordinates  $(X_1, Y_1)$  and  $(X_2, Y_2)$  is

$$[(x_1 - x_2)^2 + (y_1 - y_2)^2]^{1/2}$$

as in the Pythagorean theorem. We have also computed the distances using the City-Block metric, where the distance between  $(X_1, Y_1)$  and  $(X_2, Y_2)$  is

$$|x_1 - x_2| + |y_1 - y_2|$$

The results obtained from the multidimensional scaling technique do not lend themselves to traditional experimental data analysis. The main

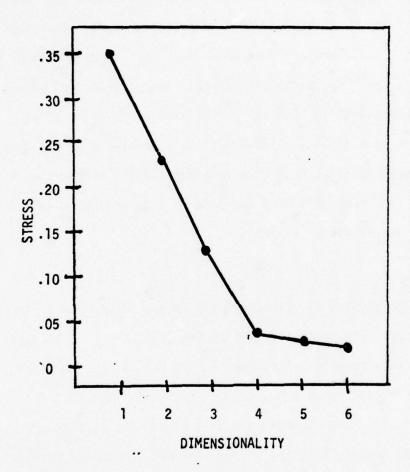


Figure 8. Diagram of stress plotted as a function of dimensionality.

The break or "elbow" in the curve at four dimensions indicates
that this is the proper number of dimensions needed to adequately
describe the psychological space.

criterion for deciding the "appropriate" dimensionality of the psychological space, and the metric which best describes that space has been consideration of stress values. Satisfactory fit with a low stress configuration are ill-defined concepts. Kruskal (1964) has provided some standard interpretations of stress values: a stress of .26 is considered poor, .05 is good, and .025 is excellent. A second criteria which must be considered along with stress values is the interpretability of the dimensions in the resulting configuration. Interpretability consists of the name or description an investigator can give to a dimension. Therefore, the analysis of the data necessarily involves subjective, qualitive considerations. Since extensive analysis is done on each subject's data the data will be presented in order to emphasize trends for "typical" subjects.

#### Results

The results are presented and discussed separately for each display type described earlier. The general format of the presentation consists of tables of stress as a function of dimensionality for typical subjects for both the Euclidean and City-Block metric. This is followed by a qualitative description of the dimensions obtained for each display type. Conclusions about the diagnosticity of the scaling metric for the purpose of assessing the relative integrality of complex integrated displays will follow.

Faces - The similarity data obtained for the subsets of faces were analyzed for up to three dimensions. One subset included 25 faces that varied in eye length and eye eccentricity. Table 3 presents stress values for this subset. The pattern of stress is typical for all of the data presented here: the Euclidean metric generally provided configurations of lower stress for a given number of dimensions than the City-Block metric. The stress values in Table 3 also fail to demonstrate an "elbow" or a

Table 3

#### Stress Values for First Subset of Faces\*

Metric	Number	of Dim	of Dimensions	
	1	2	3	
Euclidean	.23	.16	.10	
City-Block	.23	.20	.14	

<sup>\*</sup>Stress values are averaged across three subjects.

dimensionality beyond which increasing the number of dimensions fails to produce a significant reduction in stress. This is also typical of all the configurations. Thus, this particular aid to interpretability cannot be utilized. Two interpretable dimensions were recovered from the subset of spaces. Figure 9 shows the two dimensional solution, for a typical subject in a Euclidean space for faces varying in eye length and eccentricity. The horizontal dimension is length and the vertical is eccentricity. Thus, numbers connected by solid lines represent stimuli with the same eccentricity, and numbers connected by dashed lines represent stimuli with the same length. If the two dimensions were perfectly noninteractive, the lines connecting the stimuli would form a rectangle, with the solid lines perpendicular to the dashed lines. The departure from perpendicularity is due largely to two factors: One is simply noise, shown by the non-systematic distortions. The second is the fact that physically similar eccentricity intervals were perceived as smaller in shorter eyes than longer eyes. This is shown by the divergence of horizontal solid lines from the first to the second eye length groups. (i.e., the groups in the left side connected by dashed lines). In addition, although all length intervals were physically equal, the perceived difference in length between the two shortest eyes (number 1 and 2 or 6 and 7, etc.) was much larger than between any other pairs of eyes adjacent in length.

A second subset of faces that were examined included 25 faces that varied in mouth curvature and nose length. Table 4 lists stress as a function of dimensionality for the two metrics. Again, the Euclidean metric gives lower stress than the City-Block. In this subset of faces, three interpretable dimensions were recovered; nose length, mouth curvature, and mouth length. Mouth length was a function of the mouth curvature parameter since the length of the mouth is defined as an arc of a circle whose radius is determined by the curvature parameter.

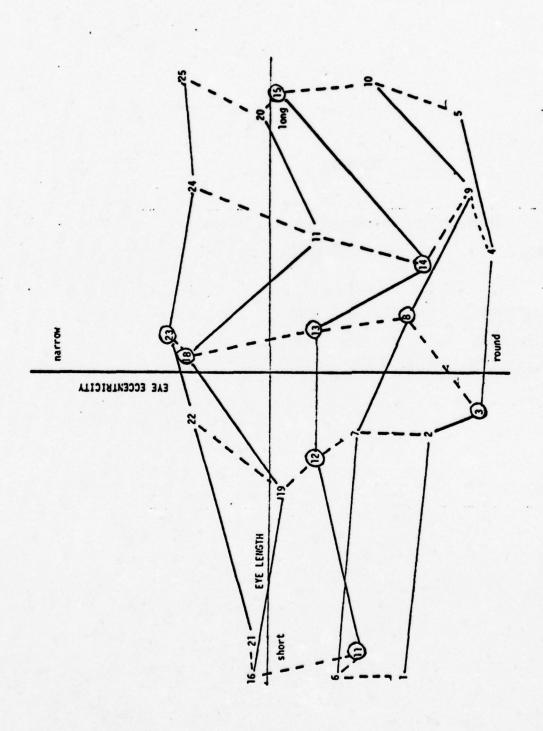


Figure 9. Two dimensional solution for the similarity data on the first subset of faces. The recovered dimensions are eye length along the horizontal axis and eye eccentricity along the vertical. The circled numbers correspond to those faces presented in Figure 3.

Table 4

Stress Values for Second Subset of Faces\*

Metric	Number o	f Dime	Dimensions	
	1	2	3	
Euclidean	.37	.19	.10	
City-Block	.37	.20	.13	

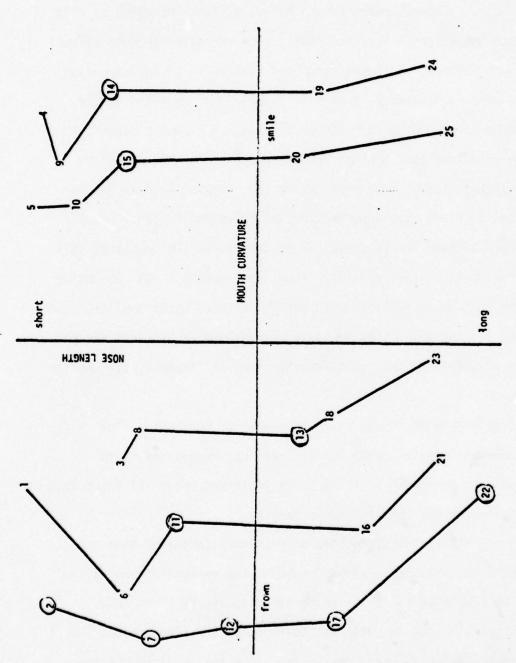
\*Stress values are for a typical subject

Figure 10 illustrates nose length along the vertical axis and mouth curvature along the horizontal. Again, this plot is for a typical subject in Euclidean space. Numbers connected by the solid lines represent stimuli with equal mouth curvatures. Physical nose length increased through stimuli one, six, eleven, sixteen, and twenty-one, and similarly for corresponding groups. There were no departures from this ordering in perceived length.

The groups beginning with stimuli one and two had frowning mouths, the stimulus three group had flat mouths, and the groups beginning with four and five had smiling mouths. The reversal in the ordering between groups one and two, and four and five occurred for the following reason. Groups one and five were extreme in the curvature parameter, so the mouths of this group were formed from smaller circles. Thus, the lengths of the mouths of groups four and five were proportionally equal, but absolutely smaller, than those of groups two and four. The mouths are perceived as less extreme in emotion. An examination of the mouth lengths shown in Figure 4 will confirm this impression.

Figure 11 examines the effect of mouth length more closely. The horizontal dimension is nose length and the vertical represents mouth length. The numbers connected by solid lines represent groups of faces with increasing nose length and constant mouth length.

A comparison with Figure 10 for the same stimuli indicates that the group beginning with stimulus three has moved to the extreme of one of the dimensions. The mouths of the stimulus three group are flat and long. While they are intermediate in value for mouth curvature, they become extreme when mouth length is being considered. The mouths of groups two and four are intermediate in length, and position in Figure 11. The shortest mouths are the groups one and five. The plots of these stimuli using the



nose length along the vertical. The circled numbers correspond to those faces presented in Figure 4. second subset of faces. The recovered dimensions are mouth curvature along the horizontal axis and Figure 10. The first two dimensions of the three dimensional solution for the similarity data on the The numbers connected by solid lines represent mouths of equal curvature.

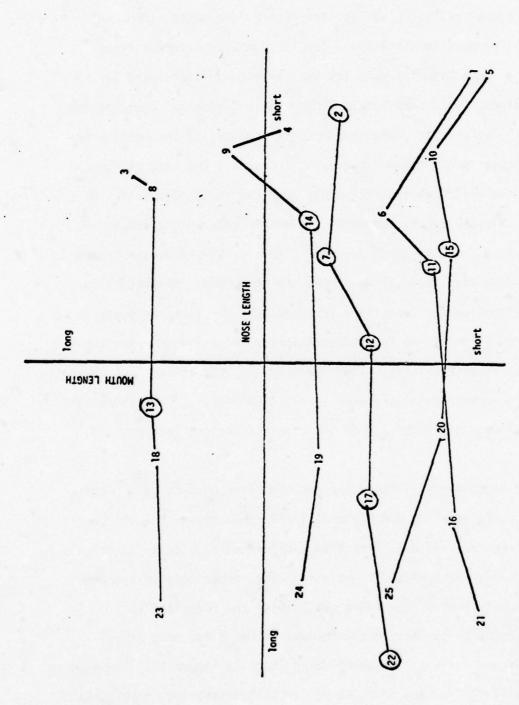


Figure 11. Dimensions 2 and 3 of the three dimensional solution for the similarity data on the second vertical. The circled numbers correspond to those faces presented in Figure 4. Numbers connected subset of faces. Nose length is represented along the horizontal axis and mouth length along the by solid lines represent stimuli of equal mouth length.

City-Block metric are generally noisier and less interpretable.

The same subsets of stimuli were tested in an upside down orientation.

The multidimensional scaling plots for the upside down faces showed no significant differences from the plots for the normally oriented faces.

Ellipses - The similarity data for the ellipses were analyzed for up to five dimensions. Data were obtained from six subjects and analyzed for five of those. The results presented here are from two of the more interpretable configurations. Table 5 presents stress as a function of dimensionality for the Euclidean and City-Block metrics for two subjects. As with the other display types, the Euclidean metric generally gives lower stress values than the City-Block metric. Also, the stress does not seem to stop decreasing significantly as dimensions are added. Theoretically, five or more dimensions are necessary to adequately describe the psychological space. However, three of the five subjects presented only one interpretable dimension, that of eccentricity. The other two subjects who will be discussed here, also gave eccentricity as a very strong dimension. In addition, their configurational output yielded one or two other dimensions that are of interest.

Figure 12 shows the two dimensions obtained from Subject 3. Eccentricity is represented along the horizontal axis and area of the ellipse is represented along the vertical. The four clusters of physically identical eccentricity groups are typical of subjects' data, regardless of the second dimension. Also typical is the large gap between the right and left eccentricity clusters, into two qualitative groups of round vs. long shape.

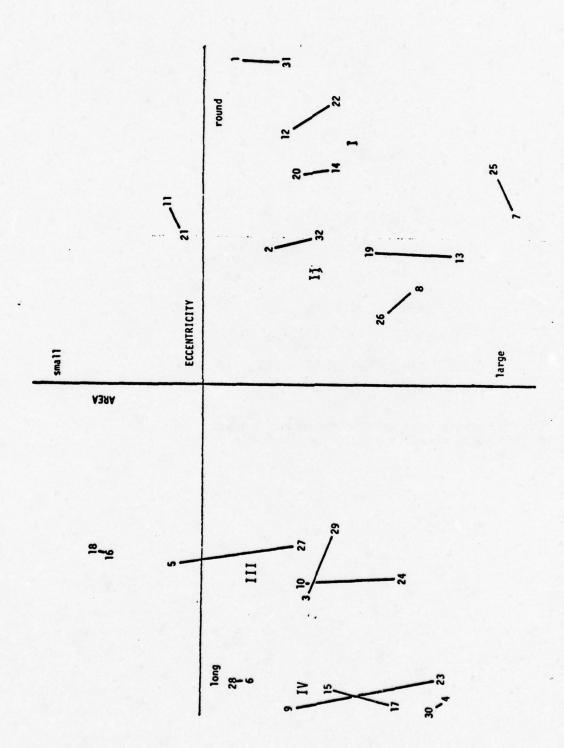
Pairs of stimuli are connected by solid lines in Figure 12. These pairs represent stimuli of the same area and eccentricity differing on position and orientation. The particular close groupings of the stimuli within the

Table 5

Stress	Values	tor	EII	ipses*

Subject	Metric	Number of Dimensions				
		2	3	4	5	
3	Euclidean	.12	.08	.06	.04	
	City-Block	.13	.12	.09	.08	
5	Euclidean	.21	.13	.09	.07	
	City-Block	.23	.17	.12	.10	

<sup>\*</sup>Two dimensions were interpretable for Subject 3, and three dimensions were interpretable for Subject 5.



city is represented on the horizontal axis and area along the vertical. The pairs connected by lines represent stimuli of the same eccentricity and area. The pairs differed in orientation and position, dimensions that were not recoverable for this subject. The groups labeled with Roman numerals represent the four clusters of eight stimuli having the same eccentricity. The stimuli are ordered Eccentri-Figure 12. Two dimensional solution for the similarity data on the ellipses from Subject 3. according to area within each eccentricity group.

pairs is impressive here because the subject claimed to be using only "size" and "shape" in making his judgments. Since the dimensions on which the stimuli within a pair differed, namely orientation and position, were specifically not incorporated in the judgments, one would expect the pairs to lie close togehter.

A final point to notice about Figure 12 is the apparent interaction between the area and eccentricity dimensions. The group of ellipses that are extremely round in shape are more "spread out" along the eccentricity axis. Similarly, within the cluster of the round ellipses, the pairs exhibit more spread along the area axis with 1-31 being the smallest and 7-25 the largest. Physically equal size differences were perceived as greater with round ellipses than long ellipses. This interaction is reminiscent of the eye length by eye eccentricity interaction described in Figure 10.

Figures 13 and 14 present the three dimensional configuration for Subject 5. This subject claimed to have noticed and used five dimensions in his judgments. However, only three were interpretable. Figure 13 presents eccentricity along the horizontal axis and vertical position in a square along the vertical axis. Again, notice that the stimuli are clustered into two eccentricity groups. The four groups defined by the physical manipulation of eccentricity are not as clear cut as in Figure 12. The vertical position dimension also splits into two groups: those stimuli above the axis were in the two high positions on the screen, and those below the axis were in the two low positions. The same split into two groups according to left and right position on the screen is apparent for the horizontal position dimension plotted against eccentricity.

Figure 14 presents the two position dimensions. Horizontal position is along the horizontal axis, and vertical position along the vertical axis. It is generally true that the position of the stimuli can be described by

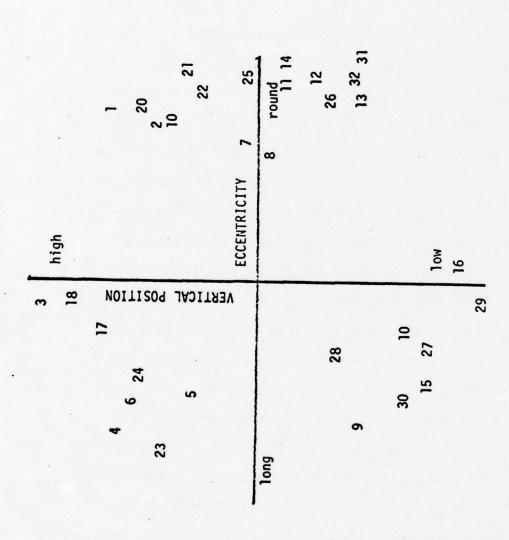


Figure 13. Dimensions 1 and 2 of the three dimensional solution for the similarity data on the ellipses from subject 5. Eccentricity is represented along the horizontal axis and vertical position within a square along the vertical axis.

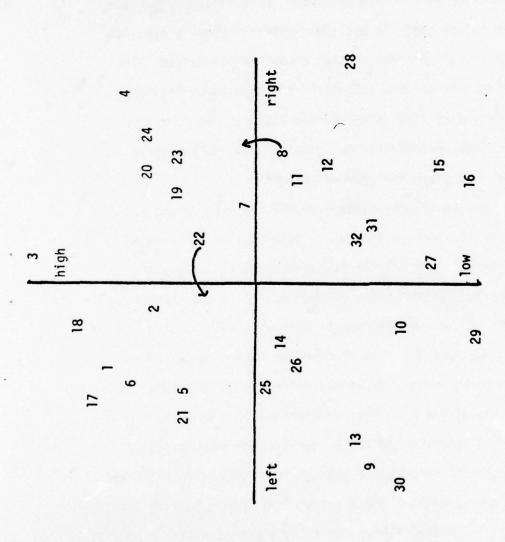


Figure 14. Dimensions 2 and 3 of the three dimensional solution for the similarity data on the ellipses horizontal axis, and vertical position along the vertical. The recovered dimensions adequately desfrom Subject 5. To aid interpretation, horizontal position in the square is represented along the cribe the four spatial quadrants on the screen except for the misplacement of stimuli 22 and 8.

their placement within one of the four quadrants formed by the two axes. The only misplaced points are numbers 22 and 8, which should be moved counter-clockwise into the adjacent quadrant.

<u>Vector Groups</u> - Table 6 presents stress values for the three polygon display types as a function of dimensionality for the Euclidean and City-Block metrics. Again notice that the Euclidean metric generally provides lower stress, but again without a noticeable "elbow" in the values. The high stress values place the configurational "fit" at somewhat less than good limiting the interpretability of the configurations. No more than three dimensions were interpretable for any display type, so the three dimensional solutions were given the greatest attention.

One feature that was abundantly clear over all the experiments was that the subjects were not simply basing their judgments on the lengths of the vectors of the figures; that is, the judgments were not in any simple way related to the physical descriptions of the figures in the terms in which they were created. Instead the overall configuration produced was the major determining factor. The type of configuration produced by the same combination of vectors changed dramatically depending on whether the stimuli were part of the spokes, polygon, or combined display type.

Subjects in general seemed to be quite sensitive to which pairs of stimuli could be brought into congruence through rotation, or rotation and reflection. They tended to cluster these pairs of stimuli. Looking for clusterings of stimuli in general turned out to be a more fruitful approach, in terms of interpretability, than attempting to interpret dimensions per se.

In fact, the polygon subset presented in Figure 16 is the only set of axes that can be interpreted. The others, Figures 15 and 17, are best described with the use of clusters of pairs of points. For example, Figure 15 presents a two-dimensional solution for the similarity data for spokes.

Table 6

Stress	Values	for	the	Vector	Group*
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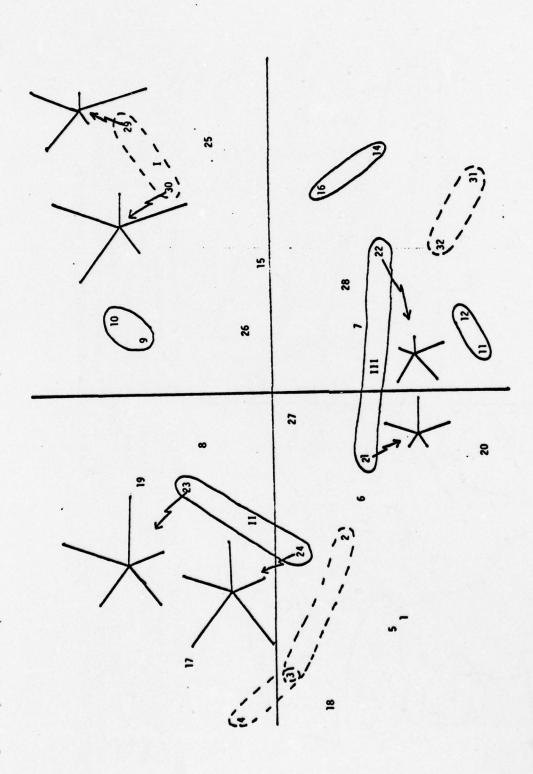
Display type	Metric	Number of Dimensions			
		2	3	4	5
Spokes	Euclidean	.27	.17	.13	.10
	City-Block	.28	.20	.14	.11
Polygons	Euclidean	.19	.14	.09	.07
	City-Block	.21	.15		
Combined	Euclidean	.27	.20	.15	.12
	City-Block	.28	.22	.18	.14

<sup>\*</sup>Stress values are for three typical subjects.

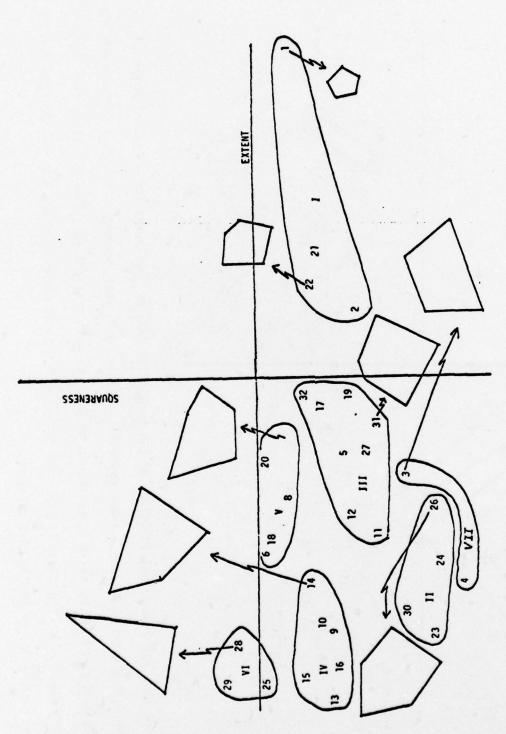
The pairs connected by solid lines are those that can be rotated and/or reflected into congruence. Examples are given for group II, which required only rotation, and group III, which needed both rotation and reflection. Pairs of stimuli that could be brought into congruence in this manner generally had smaller resulting interpoint distances than pairs that could not be brought into congruence but were made up of the same components.

Figure 15 also illustrates another important configurational aspect of the spokes. Stimuli that were very nearly size transformations of each other (i.e., which varied by I unit along each of four dimensions as from 13333 to 14444, or 31134 to 42244) were judged as highly similar, and often were clustered in the plots. An example of this is group I in Figure 15. Thus size of stimuli was taken into account, but in the context of the entire configuration it was used to group similar-shaped stimuli rather than spread stimuli out along a size dimension.

Again, overall qualitative configurational aspects appear to be the most salient attributes of the displays. Spatial "extent" of the display is represented along the horizontal axis, and "squareness" along the vertical. Several distinct clusters also emerged. Stimulus #1, shown in the figure, was the only regular polygon and also the smallest figure. It was seen as widely different from all other stimuli. In addition it was part of a widely dispersed cluster, labelled I, which could be described as small and regular. Several other clusters were describable in the plot. These are listed with Figure 16. The clusters seem to arrange themselves along two dimensions. One dimension, termed extent, has to do with the size and elongation of the figures. The other dimension has prototypical figure types as extremes: triangularity vs. squareness.



each other. Some prototypical examples of stimuli are represented in the figure. See the text for Stimuli connected by solid lines represent those stimuli that are rotation/reflection transforms of Stimuli clustered by dashed lines represent those stimuli that are size transforms of each other. Figure 15. Two dimensional solution for the similarity data on the spokes for a typical subject. an explanation of the labeled clusters.



with a bite out" polygons, group IV is four-sided non-symmetrical polygons, group V is non-symmetrical polygons tending toward 4-sidedness, group VI is large, triangular polygons, and group VII is 4-sided, I represents the small and Iwo qualitative dimensions, extent along the horizontal axis and squareness along the vertical axis, III is pointed "squares Figure 16. Two dimensional solution for the similarity data on the polygons from a typical subject. Several prototypical examples are presented in the figure. regular polygons, group II is pointed "squares with a hat" polygons, group group The stimuli are clustered into describable groups: symmetrical polygons. were recovered.

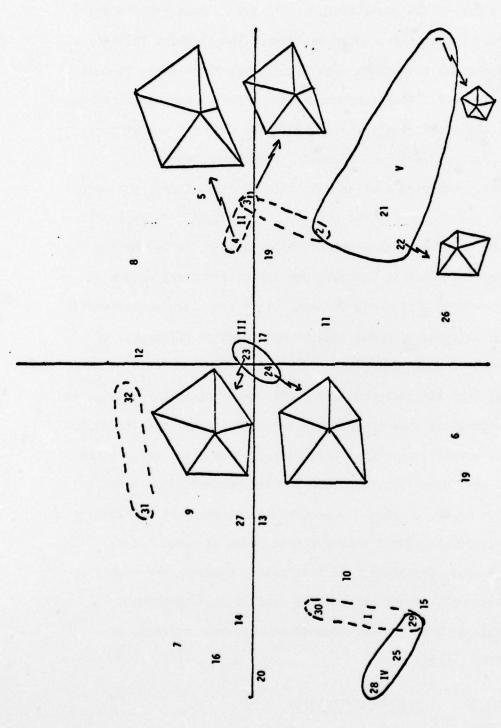
Configurations for the combined display in two dimensions are presented in Figure 17. No clear dimensional interpretations were apparent; however, the stimuli again tend to cluster in various ways. The clusters include configurational aspects of the spokes such as size transformations (groups I and II) and rotation/reflection congruence (group III). The clusters also include aspects of shape and regularity demonstrated with the polygons. Group IV is triangular and large and Group V is small and regular.

Several subjects commented that an attribute of depth seemed to emerge spontaneously with some stimuli in the polygon and combined display types. However, there is no systematic evidence of this attribute in any of the recovered scaling plots. This is probably due to the arbitrary nature of the polygons for providing a property of depth since there was no systematic attempt to generate polygons with the idea of manipulating the degree of salience of the emergent depth attribute.

It is apparent from the preceding discussion that the specifications for the physical dimensions used to generate the vector group are inadequate for determining the rules of psychophysical correspondence for these three display types. We have been forced to describe the psychological space in terms of qualitative shape variables. Conceivably, it would be possible to specify the obtained psychological attributes in terms of quantitative combinations of physical dimensions. At this point, however, the specified physical dimensions simply do not reflect the complex configurational aspects of the displays which present themselves as psychologically very salient and compelling attributes.

# GENERAL DISCUSSION

The major conclusion that can be made from the data presented in this report is that the simplest multidimensional scaling techniques of the kind described here are not diagnostic for determining the dimensional structure



V represents a cluster of small, regular stimuli. Several prototypical examples are presented in the figure. forms of each other. Groups III and IV represent stimuli that are rotation/reflection transforms. Group Figure 17. Two dimensional solution for the similarity data on the combined group from a typical subject. spokes and polygons. For example, groups I and II represent clusters of stimuli that are size trans-The stimuli are best represented by clusters that form a combination of clusters observed for the

of complex displays of high dimensionality. This conclusion is based on a number of aspects of the available data:

- 1) The similarity ratings given for all displays types by all subjects were fit better (in terms of lower stress values) by the Euclidean rather than the City-Block metric. On the face of it, this would lead us to conclude that all of our displays were unanalyzable; a conclusion that is not intuitively compelling.
- 2) The most interpretable and useful set of data was obtained with the subsets of faces which were allowed to vary on only two dimensions at a time. The two physical dimensions were readily recoverable in the psychological space. In addition, it was possible to note the existence of interactions between dimensions, and the potential for the effect of emergent dimensions.
- 3) The data was much less clear and open to interpretation when 5-dimensional displays were investigated. With the polygon figures it is particularly apparent that the input physical dimensions were not recoverable in the psychological scaling plots. Instead, configurational aspects such as shape and regularity emerged. It is obvious that a much more complicated combination of physical variables is necessary to determine the psychophysical correspondence between physical dimensions of the polygons and their psychologically perceived attributes.
- 4) The ellipse data demonstrate several problems with the multidimensional scaling technique that may prove insurmountable for its use as a diagnostic technique in this context. Subjects have a great deal of difficulty in dealing with five dimensions when making similarity judgments. Consequently their judgments can contain an unacceptable amount of noise that contributes to the non-interpretability of the data. Another difficulty lies in the fact

that multidimensional analysis programs were designed to operate with one metric to describe the dimensional structure of all the dimensions comprising a display. Thus if a display is composed of combinations of integral and separable dimensions, such a structure will not be readily described with traditional multidimensional scaling programs.

There are both practical and theoretical implications of our conclusion that simple forms of scaling analysis do not determine the dimensional structure of complex displays. From the practical side, it was our purpose in conducting these studies to arrive at psychophysical data that would be predictive of important performance measures such as reaction time or information transmission. In other words, in dealing with tasks that involve encoding information from complex displays we would rather not have to rely on simply cataloguing the performances themselves. We would rather prefer to predict performance on the basis of the psychophysical characteristics of the displays. It was our belief on the basis of existing literature that simple scaling techniques and the metric that results from them would indicate the independence of the processing of information across dimensions. While the data in this report indicate that this belief is incorrect, we cannot give up our goal of specifying the psychophysical structure of multidimensional displays for the purpose of prediction. Rather, we must turn to more complex and more useful modes of psychophysical analysis. In particular, we must turn toward analyses that more directly specify the mapping of known and manipulable physical display dimensions into psychologically perceivable attributes.

Analyses of this type have been developed and are described in Somers and Pachella (1977). The successful representation of complex information in an integrated display depends on the knowledge and exploitation of naturally occurring interdimensional relationships. Sets of dimensions

vary in separability, the extent to which the perception of each dimension is independent of co-occurring dimensions. Nonseparability due to integrality among dimensions can be distinguished from nonseparability due to masking and distraction. Integrality may result from two separate types of dimensional relationships, interaction and combination. The former is a general form of interaction whereby the appearance of one dimension is modified by the presence of a second dimension when the subject is called upon to judge the overall similarity of two displays. This form of integrality can usually be detected and analyzed with ordinary multidimensional scaling techniques. However, combination involves assessing whether or not a subject can compensate for this interaction when called upon to do so. This form of integrality can only be detected by means of multidimensional scaling under appropriate instructions to the subject and in comparison to scaling configurations that are obtained using regular multidimensional scaling techniques.

Either of these forms of integrality could be present regardless of the form of the scaling metric (either Euclidean or City-Block). Additionally, the specification of which form of integrality is present is important since combination potentially would have more drastic consequences than interaction, since it can only be overcome by connecting the physical display variables themselves. Thus, multidimensional scaling, when used appropriately, can be a valuable resource in diagnosing the dimensional structure of complex integrated displays.

From a theoretical point of view, the present data demonstrate the inadequacy of identifying the scaling metric too closely with a mode of perceptual processing. The previous literature, most notably Garner (1974), has equated the presence of the City-Block metric with separable dimensions and the Euclidean metric with integral dimensions. The present data,

together with the analyses developed by Somers and Pachella (1977) indicate, however, that integrality is a function of the mapping of the physical dimensions into psychological dimensions rather than being a property of physical dimensions themselves. The key feature that needs to be understood with regard to defining integrality is simply the ability of subjects to separate out independent sources of information from the perceived stimulus array. This can only be done if the physical display dimensions are compatibly mapped into the attributes that define the psychological space. Therefore, these mappings need to be carefully specified for any display for which one would attempt to code information from any applied setting.

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19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

multidimensional scaling psychological space complex integrated displays integral dimensions

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Five types of complex integrated displays were subjected to multidimensional scaling analyses. The display types were selected to be representative of a variety of characteristics that can result when dimensions are combined in an integrated fashion. These characteristics included perceptual separability, familiarity, emergent properties and perceptual interaction among dimensions. Of primary interest was the question of whether or not the Minkowski scaling metric would be

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diagnostic or predictive of any of these characteristics, as previous literature had indicated. The results showed that in virtually all cases the Euclidean metric produced better fits than the City-Block metric. The qualitative interpretability of the individual dimensions of the splay proved to be of much greater utility for assessing perceptual characteristics. Representative analyses of individual subject data are presented and the implications of the results for display design are discussed.

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